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ABSTRACT

In this paper, formulas for computing the weights that maximize the reliability of a test with multiple parts are derived using a congeneric model. A direct derivation for the three-part test and case and a two-step derivation for the n-part case are presented, and results for these two approaches are shown to be consistent for the three-part case. The computations of the formulas are rather simple and are all based on the variance-covariance matrix of the part scores. Two examples are given to show the computations and the usefulness of the formulas. One used data from the American College Testing Program's Work Keys listening assessment for 1,793 examinees and 3 test items. The other used the same data for all six items in the test. These formulas apply not only to performance assessment situations but also to other testing situations where each subtest may contain multiple items. (Contains 2 tables and 11 references.) (Author/SLD)

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Weights that Maximize Reliability Under a Congeneric Model for Performance Assessment

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Abstract

In this paper, formulas for computing the weights that maximize the reliability of a test with multiple parts are derived using a congeneric model. A direct derivation for the three-part and case and a two-step derivation for the *n*-part case are presented and results for these two approaches are shown to be consistent for the three-part case. The computations of the formulas are rather simple and are all based on the variance-covariance matrix of the part scores. Two examples are given to show the computations and the usefulness of the formulas.

Key Words: maximizing reliability, congeneric model, tau-equivalent parts, composite score, differential weighting.

Weights that Maximize Reliability Under a Congeneric Model for Performance Assessment

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The rising popularity of performance assessment in recent years has posed some new chanllenges for psychometrics. Performance assessment instruments typically consist of more than one task or prompt. The tasks often form a content structure and are not interchangeable. In those situations, the tasks are parallel to subtests in more traditional standardized tests. As is often done for more traditional tests, different weights are assigned to these tasks in calculating a composite score. The weighting scheme can be designed based on different considerations such as content validity (importance), testing time, and reliability. Though the decision about the final weights may depend on several different factors, knowing the weights that maximize reliability can facilitate choosing weights. (For simplicity in expression, the weights that maximize reliability will be referred to as the optimal weights.) The purpose of this paper is to derive formulas for such weights that are potentially useful in performance assessments and other assessment settings.

Previous research has studied ways of finding the optimal weights of the composite score for tests that have subtests. This research can be organized into three categories. The first category (Thompson, 1940; Mosier, 1943; Peel, 1947) uses the classical test theory formulation for composite score reliability for a test battery. In this situation, the reliability of each subtest can be estimated using classical test theory methods such as internal consistency indices. The second category (Joe & Woodward, 1976; Conger, 1974) uses multivariate generalizability theory to find weights that maximize the reliability of the test battery composite score. Solutions for these two categories involve finding the largest eigenvalue and the associated eigenvector for a certain matrix, and so the solution does not have a closed form. Also, these methods generally require that the subtests contain multiple items in order to estimate subtest reliability or variance components. The third category (Kaiser & Caffrey, 1965; Bentler, 1968) uses factor analytical methods to find

weights for each individual item to maximize the internal consistency reliability of the test. These methods involve estimating communalities and do not have a closed form because they also require solving for the largest eigen value and associated eigenvector for a certain matrix.

The unique situation of performance assessment is that each 'subtest' generally consists of only one item. This makes the first two categories of the previously described methods difficult to implement. The third category is also not very useful because of its computational complexity. The procedure proposed here assumes a congeneric model for the test. The congeneric model states that the items are measuring the same construct but that their true score variances and error score variances may differ.

Define X as the total observed score on a test that has n parts, X_i, E_i as the observed score and error score for part i. Under the congeneric model, the test scores can be expressed as follows:

$$X = X_1 + X_2 + \cdots + X_n \text{, where}$$
$$X_1 = \lambda_1 T + E_1$$
$$X_2 = \lambda_2 T + E_2$$
$$\vdots$$
$$X_n = \lambda_n T + E_n,$$

and the λ_i's are the congeneric coefficients.

It is assumed that all of the λ_i's are positive (if not, one can reverse the scale to make them positive), that $\sum_i \lambda_i = 1$, and that all of the error variances, $\sigma^2_{E_i}$'s, are not equal. The reliability formulas under a congeneric model are summarized in Feldt and Brennan (1989, p. 115). The expression for the reliability coefficient is much more complicated when the test has more than three parts than when it has only three parts. Therefore alternative procedures for deriving the optimal weights must be used when a test has more than three parts. First a derivation for the three-part case will be given. For the more than three-part case, a two-step derivation is given, and the

two-step derivation will be shown to give the same result as the direct derivation in the three-part case.

A Derivation for the Three-Part Case

The reliability coefficient for a three-part test under a congeneric model is given by (Kristof, 1974; Feldt & Brennan, 1989):

$$\rho_{XX'} = \frac{\left(\sigma_{12}\sigma_{23} + \sigma_{12}\sigma_{13} + \sigma_{13}\sigma_{23}\right)^2}{\sigma_{12}\sigma_{23}\sigma_{13}\sigma_X^2} , \qquad (1)$$

where σ_{ij} is the covariance between part i and j and σ_i^2 is the variance part i. Let

$$Y = w_1X_1 + w_2X_2 + w_3X_3 . \qquad (2)$$

where the w_i's are weights. Usually, it is assumed that the weights sum to unity, but here for the convenience of a solution expressed below, the weights are not assumed to sum to one. Because multiplying the weights by a constant does not change the value of the reliability, the weights may be standardized to sum to one after they are found . The reliability of Y is

$$\rho_{YY'} = \frac{c\left(w_1\sigma_{12}\sigma_{13} + w_2\sigma_{12}\sigma_{23} + w_3\sigma_{13}\sigma_{23}\right)^2}{\left(w_1^2\sigma_1^2 + w_2^2\sigma_2^2 + w_3^2\sigma_3^2 + 2w_1w_2\sigma_{12} + 2w_1w_3\sigma_{13} + 2w_2w_3\sigma_{23}\right)} , \qquad (3)$$

where $c = 1/(\sigma_{12}\sigma_{13}\sigma_{23})$ is a constant which can be omitted in the process of finding the optimal weights.

One approach to solving this problem is to take the first partial derivatives with respect to w_1, w_2, and w_3. Then set the derivatives equal to zero and simultaneously solve for w_1, w_2,

and w_3. To check if the results truly maximize the reliability, either the second derivatives can be taken and checked to see if they are negative at those solutions, or they can be empirically verified with some test data. It turns out the derivatives are too complicated to be presented in this paper. The equations will involve quadratic terms of the weights, which render them almost impossible to solve. But there is another indirect approach for solving this problem, and it is much simpler to present. This approach maximizes the numerator of the right side of Equation 3 while holding the denominator to be an arbitrary constant. If the relation between the weights is found not to depend on this constant, then this relation maximizes the reliability coefficient. As stated earlier, only the relation between the three weights, not the absolute value of the weights, affects the reliability coefficient. Maximizing this numerator is equivalent to maximizing the term inside the parenthesis because this term is positive. Using a Lagrange multiplier, the problem becomes finding the relative values of the weights that maximize

$$f = w_2\sigma_{12}\sigma_{23} + w_1\sigma_{12}\sigma_{13} + w_3\sigma_{13}\sigma_{23} - \lambda(w_1^2\sigma_1^2 + w_2^2\sigma_2^2 + w_3^2\sigma_3^2 + 2w_1w_2\sigma_{12} + 2w_1w_3\sigma_{13} + 2w_2w_3\sigma_{23} - d) \,, \tag{4}$$

where λ is the Lagrange multiplier, and d is a constant at which the denominator of the Equation 3 is fixed.

Taking partial derivatives of f with respect to w_1, w_2, and w_3 and setting them to zero yields

$$\sigma_{12}\sigma_{13} - \lambda\left(2\sigma_1^2 w_1 + 2w_2\sigma_{12} + 2w_3\sigma_{13}\right) = 0 \tag{5}$$

$$\sigma_{12}\sigma_{23} - \lambda\left(2\sigma_2^2 w_2 + 2w_1\sigma_{12} + 2w_3\sigma_{23}\right) = 0 \tag{6}$$

$$\sigma_{13}\sigma_{23} - \lambda\left(2\sigma_3^2 w_3 + 2w_1\sigma_{13} + 2w_2\sigma_{23}\right) = 0 \,. \tag{7}$$

Solving (5) for λ and substitute this expression into (6) and (7) yields the following two equations:

$$w_2 = \frac{\sigma_1^2\sigma_{23} - \sigma_{12}\sigma_{13}}{\sigma_2^2\sigma_{13} - \sigma_{12}\sigma_{23}} w_1 \quad (8)$$

$$w_3 = \frac{\sigma_1^2\sigma_{23} - \sigma_{12}\sigma_{13}}{\sigma_3^2\sigma_{12} - \sigma_{13}\sigma_{23}} w_1 \quad (9)$$

for the three unknowns w_1, w_2, and w_3. Note that this set of relationship does not depend on the constant *d*, which indicates that any set of weights that satisfies this set of relationships is optimal. Using *f*, *g*, and *h* as subscripts for the three parts and letting f denote any one of the three parts, then the expression .

$$w_f = \left(\sigma_f^2\sigma_{gh} - \sigma_{fg}\sigma_{fh}\right)^{-1}, \quad (10)$$

satisfies Equations 8 and 9.

It can be seen that if the variances and covariances for all three parts are equal (which corresponds to the parts being parallel except for possible mean differences) , then equal weights are optimal. The formulas for optimal weights suggest that a part will get high weight if it has a small variance but large covariances with the other two parts.

Example One:

The following example used data from one form of the Work Keys Listening assessment (ACT, 1994). The data contain item scores for 1793 examinees who took six writing items. This example used the first three items in the test. Table 1 contains the results. The optimal weights are approximately .2, .6, and .2. The reliability increases from 0.618 for the unweighted sum to 0.677 for the weighted sum with the optimal weights. The increase is sizable, suggesting that the optimal weights might be useful in this case.

A Two-Step Derivation for the n-Part Case

The reliability coefficient for a test of four or more parts (assume there are n parts) is given by (Gilmer & Feldt, 1983; Feldt & Brennan, 1989) as:

$$\rho_{XX'} = \left(\frac{\left(\sum D_f\right)^2}{\left(\sum D_f\right)^2 - \sum D_f^2} \right) \left(\frac{\sigma_X^2 - \sum \sigma_f^2}{\sigma_X^2} \right), \qquad (11)$$

where $D_f = \dfrac{\sum_g \sigma_{fg} - \sigma_{ff} - \sigma_f^2}{\sum_g \sigma_{lg} - \sigma_{ff} - \sigma_l^2}$, and row l is the row of the variance and covariance matrix with the largest sum of inter-part covariances. When $f = l$, $D_f = 1.0$.

This expression is so complicated that it is impossible to use the previous approach to find the optimal weights. A two-step approach to this problem is thus proposed here. In the first step, we will find a set of weights that makes the parts have equal true score variances, i.e., the parts become tau-equivalent. In the second step, we will find a set of optimal weights for the tau-equivalent model. The weights for each item thus obtained from these two steps are multiplied together to get the final weights for the original scores. It will be shown below that the weights thus obtained are optimal for the original item scores.

Theorem 1: For a test that has n parts with subscores $X_1, X_2, \cdots, X_n$, it is assumed that there exists a set of optimal (maximizing reliability) weights. If we transform X_i's to Y_i's by multiplying them with an arbitrary set of non-zero weights, $Y_i = \dddot{w}_i X_i$, i=1, 2,$\cdots$, n and if a set of weights $\ddot{w}_1, \ddot{w}_2, \cdots, \ddot{w}_n$ are optimal for $Y_1, Y_2, \cdots Y_n$. Then it is claimed that the set of weights $w_i = \dot{w}_i \ddot{w}_i$, i=1, 2,$\cdots$, n, are optimal for $X_1, X_2, \cdots, X_n$.

Proof: By assumption, there is a set of optimal weights for $X_1, X_2, \cdots, X_n$. Denote them as $w_1^o, w_2^o, \cdots, w_n^o$, and let $\rho_{\max}$ be the maximum reliability.

Because $\ddot{w}_1, \ddot{w}_2, \cdots, \ddot{w}_n$ are optimal for $Y_1, Y_2, \cdots Y_n$, the reliability of the left side of

the equation

$$w_1^{-} Y_1 + w_2^{-} Y_2 + \cdots + w_n^{-} Y_n = w_1^{-} w_1^{'} X_1 + w_2^{-} w_2^{'} X_2 + \cdots + w_n^{-} w_n^{'} X_n \qquad (12)$$

is also ρ_{max}. Because if it is less than ρ_{max}, then there exists another set weights $w_1^{o}/w_1^{'}, w_2^{o}/w_2^{'}, \cdots, w_n^{o}/w_n^{'}$, which when applied to $Y_1, Y_2, \cdots Y_n$ would make the reliability to be ρ_{max}, and this contradicts the condition that $w_1^{-}, w_2^{-}, \cdots, w_n^{-}$ are optimal for $Y_1, Y_2, \cdots Y_n$. If it is greater then ρ_{max}, then by Equation 12, the right side of Equation 12 also has reliability greater than ρ_{max}, which contradicts the condition that ρ_{max} is the maximum reliability of original parts using the optimal weights. Therefore, the left side of Equation must have reliability equal to ρ_{max}.

By Equation 12, we have that the weights $w_1, w_2, \cdots, w_n$ are optimal for $X_1, X_2, \cdots, X_n$., because the right side of Equation 12 also has reliability equal to ρ_{max}. This completes the proof.

The two-step derivation for finding the optimal weights for am *n*-part test is described below.

Step One:

If we can estimate the λ_i's for each item, the inverse of the λ_i's are the weights that make the transformed part scores tau-equivalent. Thus, the step one weights are

$$w_i^{'} = 1/\lambda_i \ , \ i=1, 2, \cdots, n. \qquad (13)$$

Now

$$Y = Y_1 + Y_2 + \cdots + Y_n, \qquad (14)$$

where

$$Y_1 = w_1' X_1 = (\lambda_1 T + E_1)/\lambda_1 = T + E_1/\lambda_1$$
$$Y_2 = w_2' X_2 = (\lambda_2 T + E_2)/\lambda_2 = T + E_2/\lambda_2$$
$$\vdots$$
$$Y_n = w_n' X_n = (\lambda_n T + E_n)/\lambda_n = T + E_n/\lambda_n$$

Step Two:

We need to find a set weights $w_1'', w_2'', \cdots, w_n''$ that are optimal for $Y_1, Y_2, \cdots Y_n$; that is, the reliability of $Z = w_1'' Y_1 + w_2'' Y_2 + \cdots + w_n'' Y_n$ is maximized. To simplify the derivation, it is assumed that this set of weights sum to one (this condition is not necessary because if we fix it to be an arbitrary constant, we will have the same final solution). We have

$$Z = \left(w_1'' + \cdots + w_n''\right)T + \frac{w_1''}{\lambda_1} E_1 + \cdots + \frac{w_n''}{\lambda_n} E_n = T + \frac{w_1''}{\lambda_1} E_1 + \cdots + \frac{w_n''}{\lambda_n} E_n \text{ , (15)}$$

$$\sigma_Z^2 = \sigma_T^2 + \frac{w_1''^2}{\lambda_1^2}\sigma_{E_1}^2 + \cdots + \frac{w_n''^2}{\lambda_n^2}\sigma_{E_n}^2 \text{ .} \quad (16)$$

Notice that the true score part is not affected by the values of the weights. Hence the reliability may be maximized by minimizing the error variances in Equation 16. Again, using the Lagrange multiplier, the problem becomes minimizing the function *f* where

$$f = \frac{w_1''^2}{\lambda_1^2}\sigma_{E_1}^2 + \cdots + \frac{w_n''^2}{\lambda_n^2}\sigma_{E_n}^2 + \lambda\left(w_1'' + \cdots + w_n'' - 1\right) \text{ .} \quad (17)$$

Taking the first derivatives of *f* with respect to the w_i'''s, setting them to be zeroand solving the resultant equations for w_i'''s yields

$$\frac{w_1''\sigma_{E_1}^2}{\lambda_1^2} = \frac{w_2''\sigma_{E_2}^2}{\lambda_2^2} = \cdots = \frac{w_n''\sigma_{E_n}^2}{\lambda_n^2} = -\lambda \text{ .} \quad (18)$$

Remove the restriction that this set of weights sum to one and let

$$w_i'' = \frac{\lambda_i^2}{\sigma_{E_i}^2} \quad , \; i=1, 2, \cdots, n \; , \tag{19}$$

Then these w_i'''s satisfy Equation 18, and combining them with Equations 13 and 19, yields the following final weights for the original scores:

$$w_i = w_i' w_i'' = \frac{1}{\lambda_i} \frac{\lambda_i^2}{\sigma_{E_i}^2} = \frac{\lambda_i}{\sigma_{E_i}^2} \quad , \; i=1, 2, \cdots, n. \tag{20}$$

The remaining problem is to find the error variances for the original score parts. Denoting the sum of the ith row of the variance-covariance matrix of the original score parts as ψ_i, yields the following two equations

$$\psi_i = \sum_j \sigma_{ij} = \lambda_i \left(\lambda_1 + \lambda_2 + \cdots + \lambda_n \right) \sigma_T^2 + \sigma_{E_i}^2 = \lambda_i \sigma_T^2 + \sigma_{E_i}^2 \tag{21}$$

$$\sigma_i^2 = \lambda_i^2 \sigma_T^2 + \sigma_{E_i}^2 \tag{22}$$

Solving them yields

$$\sigma_{E_i}^2 = \frac{\sigma_i^2 - \lambda_i \psi_i}{1 - \lambda_i} \; . \tag{23}$$

Substituting the right side of Equation 23 into Equation 20, yields

$$w_i = \frac{\lambda_i (1 - \lambda_i)}{\sigma_i^2 - \lambda_i \psi_i} \; . \tag{24}$$

Noting that $\sum_{j \neq i} \sigma_{ij} = \psi_i - \sigma_i^2 = \lambda_i (1 - \lambda_i) \sigma_T^2$ also yields

$$w_i = \frac{\psi_i - \sigma_i^2}{\sigma_i^2 - \lambda_i \psi_i} \quad , \; i=1, 2, \cdots, n \; . \tag{25}$$

Equations 24 and 25 are not equivalent, but they differ only by a constant σ_T^2, so they both represent the optimal weights.

To complete the solutions, formulas for the λ_i's are needed. Gilmer and Feldt (1983). provide the solutions for the λ_i's.

$$\lambda_i = \frac{D_i}{\sum_j D_j} \quad , \; i=1, 2, \cdots, n. \tag{26}$$

All the computations for the weights are based on the variance-covariance matrix and are within the capability of a hand calculator.

Example Two:

The following example used the same data as used in the previous example for the three parts. This example used all six items in the test. Table 2 contains the results of the computation. Item 5 gets the largest weight, followed by item 4 and item 6. The reliability increases from 0.751 for the unweighted sum to 0.796 for weighted sum with the optimal weights. This increase is moderate but is still valuable in this setting.

It is shown in the next part that Equation 25 gives the same results as Equation 10 in the three-part case. From Feldt and Brennan (1989), we have:

$$\lambda_f = \left(\frac{\sigma_{gh}}{\sigma_{fg}} + \frac{\sigma_{gh}}{\sigma_{fh}} + \frac{\sigma_{gh}}{\sigma_{gh}} \right)^{-1} \; . \tag{27}$$

Substituting this equation into Equation 25 gives

$$w_f = \frac{\sigma_{fg} + \sigma_{fh}}{\sigma_f^2 - \dfrac{\sigma_f^2 + \sigma_{fg} + \sigma_{fh}}{\dfrac{\sigma_{gh}}{\sigma_{fg}} + \dfrac{\sigma_{gh}}{\sigma_{fh}} + \dfrac{\sigma_{gh}}{\sigma_{gh}}}} = \frac{\sigma_{fg}\sigma_{fh} + \sigma_{fg}\sigma_{gh} + \sigma_{fh}\sigma_{gh}}{\sigma_f^2\sigma_{gh} - \sigma_{fg}\sigma_{fh}} \qquad (28)$$

The numerator of Equation 28 is the same for all the three weights, and thus can be dropped from the formula. It then gives the same expression as Equation 10.

Discussion

This paper gives two formulas for computing the weights that maximize test reliability, one for a three-part test, the other for a general case. It was shown that these two formula are consistent in the three-part case. There are some potential advantages for these formulas. First of all, they are easy to compute. Second, they enable us to gain insight into the factors that contribute to high or low weight for a particular part.

A congeneric model is used in the derivation, which implies that if the situation is such that the congeneric model is grossly not applicable, then these formula are probably also not applicable.

The decision on what weights to use may depend on a number of factors of which maximizing reliability may be just one. The weights that maximizing the reliability may provide a good reference for determining what weights should actually be used. Also the computations of the weights are only based on the sample data which contain sampling error. It is advisable to estimate the weights based on more than one sample and compare the results if multiple samples are available.

A final note is that these formula not only apply to performance assessment situations where they may be most useful, but that they also apply to other testing situations where each subtest may contain multiple items. They also apply to tests that contain both multiple-choice type items and constructed response type items. Because of the simplicity of the computations, these

formulas should be generally useful in situations where weighting based on reliability is a relevant concern.

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Table 1. Computations for the three-part example.

Item	The variance-covariance matrix			Row sum	Cov. sum	Lambda	Weights
1	7.388	2.373	1.207	10.968	3.580	0.390	0.197
2	2.373	4.241	1.252	7.866	3.625	0.404	0.585
3	1.207	1.252	3.066	5.526	2.459	0.206	0.218

Table 2. Computations for the six-part example.

Item	The variance-covariance matrix						Row sum	Cov. sum	Lambda	weights
1	7.388	2.373	1.207	1.114	1.886	1.283	15.250	7.862	0.164	0.076
2	2.373	4.241	1.252	1.084	1.343	1.060	11.353	7.112	0.147	0.130
3	1.207	1.252	3.066	1.095	1.057	1.147	8.824	5.757	0.116	0.133
4	1.114	1.084	1.095	4.199	2.266	2.717	12.474	8.275	0.173	0.191
5	1.886	1.343	1.057	2.266	4.151	2.841	13.543	9.392	0.205	0.323
6	1.283	1.060	1.147	2.717	2.841	5.759	14.807	9.048	0.195	0.148